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PadYi: Ensembled CNN-Transformer Attention Based Framework for Optimizing Paddy Cultivation Management and Yield Estimation

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***Abstract*—Paddy Rice cultivation in paddy fields, encompassing approximately 167 million hectares globally, serves as a critical staple for over half of the world's population and plays a pivotal role in global food security. However, this agricultural practice faces significant challenges, including water scarcity, climate change impacts, and inefficient farming methods, which collectively jeopardize its sustainability and productivity. This research introduces a novel self-curated dataset, PadiFier, and presents a comprehensive multi-stage framework that leverages advanced machine learning techniques, including Convolutional Neural Networks and Transformers. The framework incorporates state-of-the-art architectures such as ResNet18, EfficientNet, SEResNeXt, DeiT, and MobileNetV3 to enhance paddy cultivation management. Our multi-stage model exhibits state-of-the-art performance, achieving high aggregate accuracy across all stages, comparable to cutting-edge technologies in agricultural image analysis. By providing real-time, precise information on crop status, health, and potential yield, this innovative technology enables farmers to make data-driven decisions, optimize resource allocation, and implement precision agriculture techniques effectively.**

Keywords—Paddy Cultivation, CNN, Transformer, ResNet18, EfficientNet, SE-ResNeXt, DeiT, MobileNetV3

I. INTRODUCTION

Paddy cultivation plays a pivotal role in India's economy and global food security, with India ranking as the secondlargest rice producer globally, contributing approximately 23 per cent of the world's rice supply. In the 2023-24 agricultural year, India produced over 129 million metric tons of rice, representing about 40 per cent of the nation's total food grain output. Additionally, India is a key player in the global rice market, exporting around 22 million metric tons, which constitutes 40 per cent of the world's rice exports[30].

However, despite its significance, paddy cultivation in India faces significant challenges that threaten its productivity and sustainability. These challenges include water scarcity, the impacts of climate change, and limited access to advanced agricultural technologies. In regions like Punjab, for example, the excessive use of water for rice farming has led to a dramatic decline in groundwater levels. Similarly, paddy farmers in Telangana grapple with unpredictable rainfall and inadequate irrigation infrastructure, which heighten the risks associated with climate variability.

To address these challenges, recent advancements in machine learning (ML) and deep learning (DL) have been harnessed to provide innovative solutions for tasks such as crop classification[10], growth stage assessment, disease detection [6,7,8,9], and yield prediction. These technologies enable the processing and analysis of large agricultural datasets, offering valuable insights that can improve crop management practices and help overcome the traditional obstacles faced in paddy farming.

This research paper introduces an Ensembled CNNTransformer-based Framework designed to optimize paddy cultivation management and yield estimation. The proposed methodology includes multiple stages of paddy crop analysis, such as identifying cultivable land, classifying crops, determining growth stages, assessing health, and estimating yields. By utilizing high-resolution imagery alongside cutting-edge deep learning models, this study aims to improve the precision and effectiveness of paddy cultivation management, with a particular focus on the Telangana region.

The research makes several key contributions, including the development of a specialized framework that could be adapted for various agricultural applications, leading to more informed decision-making, reduced resource waste, and higher crop yields. The findings are expected to support policymakers, agronomists, and farmers in implementing precision agriculture techniques[30], thereby promoting sustainable farming practices and enhancing food security at both regional and global levels.

The main contributions of this research include:

1) Paddy Cultivation Enhancement: Development of an Ensembled CNN-Transformer-based Framework for

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optimizing paddy cultivation management and yield estimation, encompassing land detection, crop classification, growth stage identification, health assessment, and yield estimation.

2) Self-Curated Dataset: Use of a self-curated dataset specifically designed for these tasks, ensuring the model's robustness and accuracy.
3) High Task Accuracy: Achievement of notable accuracy, especially with CNN and Transformer based architecture, which reached 97 per cent in growth stage identification and effectively assessed crop health.

The structure of this paper is as follows: Section 2 reviews existing research on paddy crop assessment and the application of deep learning in agriculture. Section 3 describes the datasets and preprocessing methods. Section 4 details the methodology and each stage of the proposed framework. Section 5 presents the experimentation and results, and Section 6 concludes with a summary and potential future research directions.

II. RELATED WORK

The application of machine learning and deep learning techniques in agricultural research has grown significantly, focusing on crop classification, growth stage assessment, disease detection, and yield estimation. Deep learning has proven particularly effective in plant disease detection [25, 22, 23]. These technologies have been employed for various aspects of field detection [10], and weed management [11].

Water scarcity concerns due to increased paddy cultivation have led to research in precision agriculture and water management technologies [8]. Studies have explored paddy cultivation prediction using deep learning on land cover variation [3], emphasizing the role of these technologies in enhancing agricultural sustainability.

Significant research has focused on the detection and classification of paddy leaf diseases. Techniques such as damaged leaf detection using image processing [4], rice leaf blast disease detection through multi-level color image thresholding [29], and the use of Convolutional Neural Networks (CNNs) for disease classification [28] have been proposed. Other works have contributed to the broader application of deep learning in agriculture, including leaf disease detection using K-meansbased segmentation and neural-networks-based classification
[7].

Recent advancements in computer vision have introduced novel architectures that could potentially enhance agricultural applications. ViT-CoMer [1] addresses limitations of plain Vision Transformer (ViT) models by incorporating convolutional multi-scale feature interactions, showing promise in dense prediction tasks. Quadrangle Attention (QA) [2] introduces a learnable quadrangle regression module to dynamically adjust the attention area in Vision Transformers, demonstrating superior ability to capture context information and model longrange dependencies.

In the realm of abstract visual reasoning, ViTCN [3] combines a Vision Transformer with contrastive networks, showcasing improved performance on complex visual tasks. For plant disease detection, ViT-SmartAgri [4] leverages Vision Transformers in a smartphone-based system, achieving high accuracy in identifying tomato leaf diseases. Similarly, a study on Java Plum leaf diseases [5] demonstrates the potential of customized ViT architectures for precise and timely disease detection.

SE-VIT [6], a hybrid network combining CNNs and transformers, has shown promise in diagnosing sugarcane leaf diseases, incorporating attention mechanisms to enhance feature learning and disease identification.

These collective contributions have paved the way for advanced deep learning frameworks that can effectively identify cultivable areas, classify crops, assess growth stages, detect crop health issues, and estimate yield. These frameworks are instrumental in enhancing agricultural management and research, providing valuable insights for farming practices.

III. DATASET

In our research on paddy crop classification, we developed a specialized dataset through a combination of automated and manual methods. This dataset was meticulously assembled by collecting images from various online sources via web scraping and manual downloads using Google Chrome.

The images were organized into two main categories: ”Paddy,” which includes a diverse range of paddy crop images, and ”Other Crops,” consisting of images representing various non-paddy crops. This clear categorization was essential for distinguishing between paddy and non-paddy crops to support effective classification. The data collection process involved using web scraping techniques to automate the extraction of relevant images from the internet, ensuring a comprehensive and varied collection. This automated approach was supported by manually downloading additional images from reliable sources to fill any gaps and enhance the dataset. The integration of these methods enabled us to assemble a comprehensive set of images representing the visual characteristics of both paddy and non-paddy crops. After collection, we performed preprocessing steps, including resizing all images to a uniform dimension of 224x224 pixels, ensuring consistent input for the models. We also normalized the pixel intensity values according to ImageNet statistics to improve model convergence. Additionally, data augmentation techniques such as rotation, flipping, and cropping were applied to enhance the dataset's variability and ensure its suitability for training and evaluating machine learning models. The labeling process involved categorizing images into ”Paddy” and ”Other Crops” using a combination of automated labeling scripts and manual verification. This approach ensured accurate classification, supported by domain expertise and visual inspection. Our dataset comprises a total of 740 images, with 340 paddy images and 400 images of other crops. The images are in formats such as .jpg, .jpeg, and .png. The carefully curated size and composition of the dataset were designed to address the limitations of standard datasets, providing enhanced diversity and specificity for paddy crop classification. This curated dataset, with its balanced representation, sets a strong foundation for training and evaluating machine learning models, offering capabilities that standard datasets may not fully provide.

IV. METHODOLOGY

A. Problem Statement

Effective management of paddy cultivation and procurement is crucial for agricultural sustainability and economic development, particularly in regions like Telangana, India, where water resources are limited. Identifying paddy cultivation areas, monitoring growth stages, and ensuring the authenticity of harvested crops are significant challenges. Traditional methods are often labor-intensive, error-prone, and lack realtime data, which highlights the need for a more efficient solution. This research introduces a comprehensive multi-stage Convolutional Neural Network (CNN) approach to address these challenges. The first stage involves the accurate identification of paddy fields and differentiation from other land cover types using high-resolution satellite imagery. This stage exploits both spectral and spatial features to distinguish paddy fields. The subsequent stage employs a finer-resolution CNN to differentiate specific paddy varieties based on their spectral signatures and morphological characteristics across different growth stages, utilizing temporal changes . To ensure the authenticity of procured paddy, the research integrates models that detect counterfeit or substandard crops by analyzing highresolution imagery for morphological anomalies. For binary classification, the ResNet18 model, pre-trained on ImageNet, was adapted by removing the final classification layer and replacing it with a new layer for predicting paddy versus non-paddy crops. This adaptation allowed for effective feature extraction using ResNet18's hierarchical features.Additionally, MobileNetV2 was used for its efficient feature extraction capabilities by leveraging only the convolutional base and average pooling. Area estimation was handled by converting pixel areas to hectares (1 hectare = 107,639.1 square feet) and predicting crop yield based on historical data for five stages of paddy cultivation. The paper, at first, begins with the detection of cultivable land, ensuring that only arable land is selected for agricultural use. Once the land is confirmed to be cultivable, the next step involves identifying the crop type. If the identified crop is paddy, the process proceeds to growth stage identification, categorizing the paddy into various growth stages such as healthy, mild, moderate, or severe. Following this, a paddy health assessment is conducted to determine whether the crop is healthy or diseased, and if diseased, to identify the specific type of disease.

The flowchart, as illustrated in Fig. 1, provides a comprehensive process for assessing paddy crop health and predicting yield.

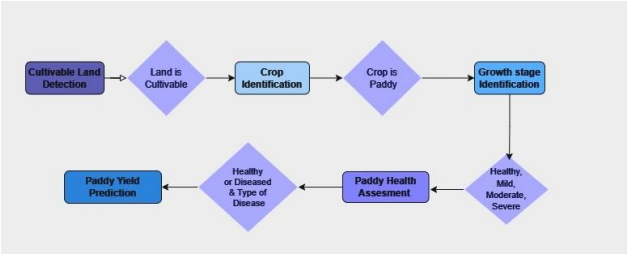

Fig. 1. Paddy Assessment Process

Finally, this information feeds into the paddy yield prediction, allowing for an informed estimate of the potential yield based on the crop's health status and growth stage. This systematic approach ensures that the paddy crops are monitored closely, and appropriate measures are taken to optimize yield.

B. Stage 1: Cultivable Land Detection

This stage aimed to detect cultivable land using a selection of pre-trained models. The dataset was made by merging our web-scraped data with the Paddy Doctor Kaggle dataset[32].

Fig. 2. Detected Cultivable Land

We employed five advanced models to derive feature vectors from these images. The classification was performed by ensembling feature vectors and applying a majority voting mechanism to determine which images were categorized as cultivable land as illustrated in Figure 2.

C. Stage 2: Paddy Crop Classification

In this stage, we focused on classifying paddy fields using a self-curated dataset PadiFier with high-resolution images labeled as either "PADDY IMAGES" or "OTHER CROPS" made by web scraping.

We fine-tuned pre-trained models for binary classification and combined their predictions to enhance accuracy as illustrated in Fig 3 and 4. Images classified as paddy fields were then further analyzed in the next stage.

D. Stage 3: Growth Stage Identification

This stage involved classifying paddy crops into four growth stages: 'Healthy', 'Mild', 'Moderate', 'Severe'. Images were preprocessed, and feature vectors were extracted using the same set of models.

Fig. 3. Paddy Crop Identification

Fig. 4. Other Crop Identification

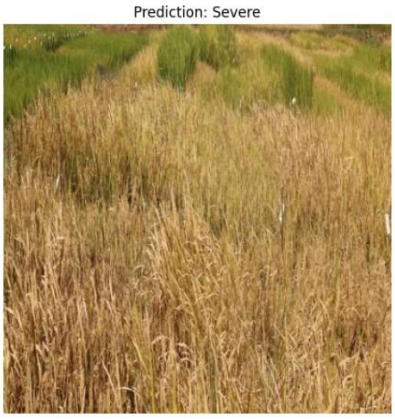

Fig. 5. Classification of Paddy Growth-Severe

Kaggle dataset on Rice In-Field Image [33] was used. These features were used to train a classifier that distinguished between the growth stages as illustrated in Fig. 5. The results were visualized to validate the classification accuracy.

E. Stage 4: Health Assessment

In this stage, we assessed the health of paddy crops, categorizing them as either healthy or diseased and further identifying specific diseases. Pre-trained models were adapted for this task, and an ensemble approach was used to combine the models' predictions.

Fig. 6. Healthy Paddy detected

Fig. 7. Diseased Paddy detected

The model's function was developed to classify the health status and detect diseases in new images as shown in Fig 6 and 7. The Kaggle Paddy Doctor dataset was used in this. Results were visualized for detailed analysis.

F. Stage 5: Yield Estimation

The final stage estimated paddy yield by analyzing the area of paddy fields from images. We calculated the field area, converted it to real-world dimensions, and estimated the yield based on historical data. Visualizations with contours highlighted the segmented areas, providing an estimate of the paddy yield as shown in Fig 8.

Fig. 8. Yield estimation

V. EXPERIMENTATION

The experimentation involved a CNN-Transformer approach for paddy crop assessment , combining thorough preprocessing with advanced deep learning techniques. Images were first resized to 224x224 pixels and normalized using ImageNet statistics to maintain consistency across the models. Then dataset was divided into training, validation, and testing subsets,where 70:10:20 ratio was used then we ensembled pre-trained models— ResNet18, EfficientNet-B0, SE-ResNeXt5032,DeiTsmall-patch16-224 , and MobileNetV3-large-100 which was then employed for detecting cultivable land. These models had their final layers replaced with identity layers to obtain high-level feature vectors. Classification was performed using cosine similarity with a threshold of 0.75 and a majority voting system. For paddy crop classification, the models were finetuned for binary classification, and predictions were aggregated to improve accuracy. During growth stage identification, feature vectors derived from the ensemble models were used to train an MLP classifier to categorize crops into 'Healthy', 'Mild', 'Moderate', 'Severe'. The health assessment stage utilized the ensemble model to classify crops as healthy or diseased and identify specific diseases, with the training guided by CrossEntropyLoss and Adam optimizer. Model performance was validated and visualized using Matplotlib. Finally, yield estimation involved calculating the field area from images, converting pixel measurements to real-world dimensions, and estimating yield based on historical data, with results illustrated through contour maps. The preprocessing steps ensure data consistency and model effectiveness throughout all stages of the paddy crop assessment.

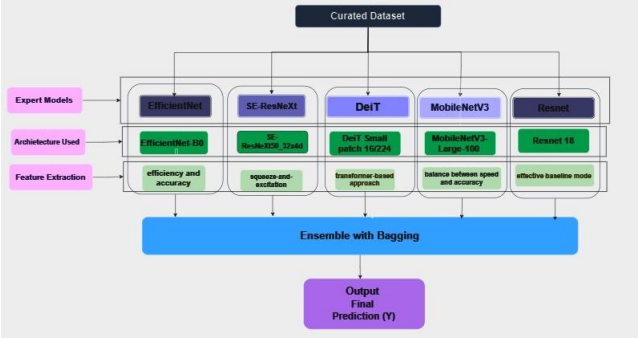

Fig. 9. Architecture of the proposed model

The Fig. 9 showcases an advanced ensemble learning approach designed to enhance prediction accuracy by leveraging the strengths of multiple expert models. The process begins with a curated dataset, which is fed into five distinct models: EfficientNet B0, SE ResNeXt 50 32x4d, DeiT Small patch 16/224, MobileNetV3-Large-100, and ResNet 18. Each model is selected for its unique architecture, such as EfficientNet's balance between efficiency and accuracy, SE-ResNeXt's squeeze-and-excitation mechanism, DeiT's transformer-based methodology, MobileNetV3's optimization for speed and accuracy, and ResNet's reliable residual connections. These models independently extract features from the dataset, and their outputs are then combined using an ensemble method with bagging. Bagging reduces variance and improves generalization by aggregating predictions from multiple models trained on different data subsets. The final prediction represents a more accurate and robust decision, benefiting from the diverse strengths of the individual models.

VI. RESULT AND DISCUSSION

The evaluation of the models provided comprehensive insights into their effectiveness across different stages .The ensemble approach, which combined efficientnet b0, seresnext 50 32x4d, deit small patch16 224, mobile netv3 large 100, and resnet18, proved to be a robust solution for classifying these stages accurately .

In Stage 1, the analysis of the input image involves determining whether it represents cultivable land. By leveraging an ensemble of pre-trained models, each image in the test set is compared to the input image using feature vectors extracted from these models. If the majority of similarity scores surpass the predefined threshold, indicating a high degree of similarity between the input image and images of cultivable land, the result will affirm that the image represents cultivable land. Conversely, if the similarity scores are predominantly below the threshold, the result will indicate that the image does not represent cultivable land.

Fig. 10 Accuracy, Precision, Recall, F1-Score and ROC Score of Stages 2,3 and 4 illustrates the performance metrics across three stages: Stage 2, Stage 3, and Stage 4. For Stage 2, the model achieves exceptionally high train accuracy at 0.9981, indicating that it learned the patterns well during training. The validation accuracy is 0.9041 while the test accuracy remains at 0.9595, suggesting good generalization to new data. Precision, recall, and F1 score are all at 0.90 or higher, reflecting a balanced and effective classification, while the ROC score is particularly high at 0.98, indicating excellent overall performance.

We achieved the training accuracy of 0.8773 in Stage 3, and the validation accuracy is 0.8286. The test accuracy is 0.8602 while precision remains at 0.91, both recall and F1 score are at 0.8602, highlighting challenges in maintaining a balance between true positives and false negatives. The ROC score of 0.9068 suggests fair classification ability and reinforces the ability of the model.

In Stage 5, the uploaded image is analyzed to estimate the paddy field area using image processing techniques, including grayscale conversion and thresholding. Based on the userprovided area in square feet, the predicted paddy yield is calculated by adjusting the estimated area and applying a standard yield rate per hectare. The processed image is then displayed with contours highlighting the segmented paddy field area, providing a visual representation of the analysis. Stage 4 demonstrates improved performance compared to Stage 3, with train accuracy increasing to 0.9743. The validation accuracy is strong at 0.9192, and the test accuracy is 0.9268, indicating that the model generalizes well to new data. Precision and recall are both above 0.92, with the F1 score slightly lower at 0.8602, showing a better balance between precision and recall than in Stage 3. The ROC score of 0.9228 further indicates robust performance in this stage.

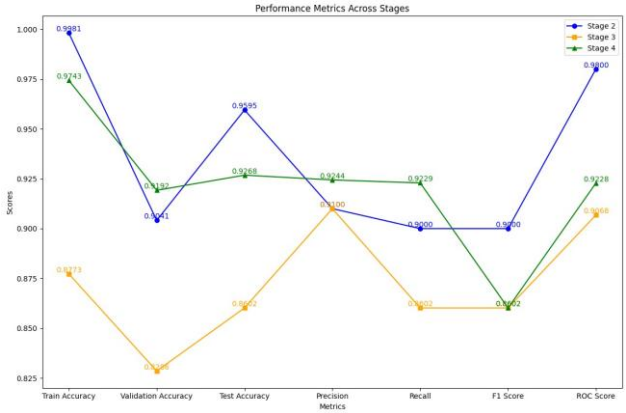

Fig. 10. Accuracy, Precision, Recall, F1-Score and ROC Score of Stages 2,3 and 4

V. CONCLUSION

This paper presents a comprehensive CNN-Transformerbased framework addressing critical challenges in paddy cultivation management, offering a unified solution for growth and crop detection, disease detection and yield estimation which has not been proposed so far. Our approach, leveraging a self-curated dataset PadiFier alongside existing resources, has demonstrated state-of-the-art performance across multiple metrics including accuracy, recall, precision and F1 score. The utilization of a custom dataset proved instrumental in uncovering novel patterns in agricultural data analysis, enhancing the model's ability to generalize across diverse conditions. The framework's robustness is evidenced by its resistance to overfitting, achieved through the implementation of ensemble techniques, specifically Bagging. This approach ensures the model's reliability and applicability across various agricultural scenarios. Our multi-stage architecture, combining CNNs and Transformers,

effectively addresses the complexities inherent in paddy cultivation management, from land detection to yield estimation.

Future research directions include the development of real-time monitoring systems to provide instantaneous insights and recommendations. Additionally, expanding and diversifying the dataset will be crucial for enhancing the model's adaptability and performance across different geographical and environmental contexts.

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